


UNIVERSITY OF TECHNOLOGY SYDNEY

Planning and Sequential Decision Making for Human-Aware Robots

by
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A thesis submitted in partial fulfilment for the
degree of Doctor of Philosophy

in the
Faculty of Engineering
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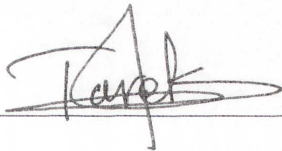
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'The greatest enemy of knowledge is not ignorance, it is the illusion of knowledge'

Stephen W. Hawking

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Abstract

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This thesis explores the use of probabilistic techniques for enhancing the interaction between a human and a robotic assistant. The human in this context is regarded as an integral part of the system, providing a major contribution to the decision making process and is able to overwrite, re-evaluate and correct decisions made by the robot to fulfil her or his true intentions and ultimate goals and needs. Conversely, the robot is expected to behave as an intelligent collaborative agent that predicts human intentions and makes decisions by merging learned behaviours with the information it currently possesses. The work is motivated by the rapid increase of the application domains in which robotic systems operate, and the presence of humans in many of these domains. The proposed framework facilitates human-robot social integration by increasing the synergy between robot's capabilities and human needs, primarily during assistive navigational tasks.

The first part of the thesis sets the groundwork by developing a path-planning/re-planning strategy able to produce smooth feasible paths to address the issue of navigating a robotic wheelchair in cluttered indoor environments. This strategy integrates a global path-planner that operates as a mission controller, and a local reactive planner that navigates locally in an optimal manner while preventing collisions with static and dynamic obstacles in the local area. The proposed strategy also encapsulates social behaviour, such as navigating through preferred routes, in order to generate socially and behaviourally acceptable plans.

The work then focuses on predicting and responding to human interactions with a robotic agent by exploiting probabilistic techniques for sequential decision making and planning under uncertainty. Dynamic Bayesian networks and partially observable Markov decision processes are examined for estimating human intention in order to minimise the flow of information between the human and the robot during navigation tasks. A framework to capture human behaviour, motivated by the human action cycle as derived from the psychology domain is developed. This framework embeds a human-robot interaction layer, which defines variables and procedures to model interaction scenarios, and facilitates the transfer of information during human-robot collaborative tasks.

Experiments using a human-operated robotic wheelchair carrying out navigational daily routines are conducted to demonstrate the capacity of the proposed methodology to understand human intentions and comply with their long term plans. The results obtained are presented as the outcome of a set of trials conducted with actor users, or simulated experiments based on real scenarios.

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Abbreviations

ADD	A lgebraic D ecision D iagrams
AI	A rtificial I ntelligence
AMCL	A daptive M onte- C arlo L ocalisation
BDD	B inary D ecision D iagrams
BN	B ayesian N etwork
CAS	C entre of A utonomous S ystems
CPT	C onditional P robability T able
CSTEP	C ontrolled S ampling and T ime E fficient P lanner
CVM	C urvature V elocity M ethod
DAC	D igital to A nalog C onverter
DBN	D ynamic B ayesian N etwork
DWA	D ynamic W indow O bstacle A voidance
EM	E xpectation M aximisation
GDWA	G lobal D ynamic W indow A pproach
HRI	H uman R obot I nteraction
ITE	I f- T hen- E lse
MDP	M arkov D ecision P rocesses
MSE	M ean S quare E rror
ND	N earness D iagram
POMDP	P artially O bservable M arkov D ecision P rocesses
PRM	P robabilistic R oad M aps
RRT	R apidly- E xploring R andom T rees
VFH	V ector F ield H istogram

Dedicated to my parents